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A simulation-based evaluation of warehouse check-in strategies for improving inbound logistics operations

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ABSTRACT

Inbound logistics is a vital step in warehouse receiving processes and has a direct impact on supply chain cost and performance. As a result of an inefficient check-in operation, the incoming trucks may experience inordinate wait times between arrival and check-in, which in turn leads to unnecessary cost to the company in the form of detention fees (a penalty for holding the truck and driver beyond the agreed upon time) and delayed delivery of subsequent consignments. Moreover, prolonged idling of queuing trucks is not environmentally sustainable as it increases the concentration of carbon dioxide (CO_2), a primary contributor to climate change, in the atmosphere. This research is motivated by a case study of one of the largest consumer goods companies in the US, which pays over a million dollars in detention fees every year. The trucks entering the facility under study encounter an average waiting time of approximately an hour. The primary objective of this paper is to minimize the detention fees paid to the carrier by enhancing the check-in process of the inbound trucks, and the secondary goal is to reduce the CO_2 emissions. Different check-in policies (staging area, dynamic dispatching rules, and automated technology) are proposed and compared to the current operations using discrete-event simulation models. The results suggest the adoption of a staging area with dynamic dispatching rule in the short-term as it requires minimal capital investment and achieves substantially lower detention fee and CO_2 emission. A more expensive yet superior alternative is the use of automated technology for check-in processing as it eliminates detention fee and reduces the CO_2 emissions from the trucks by 80%. The modeling approach and proposed dispatching rules are generic and can be adopted by any facility characterized by long waiting time for check-in and high detention fees.

1. Introduction

As we move more towards an economy driven by service systems, logistics and transportation come to the forefront, as they are one of the key drivers of supply chain. In 2016, the expenditure in the US logistics and transportation industry totaled $1.4 trillion, which accounted for 7.5% of the annual GDP [1]. Moreover, trucks alone moved more than 10.4 billion tons of freight, which tallied to $281.4 billion in trucking revenue [1]. For this amount of freight to be moved efficiently, the warehouse receiving and shipping process (truck check-in, loading/unloading, truck check-out) must have a smooth flow without causing any unnecessary delays in the procedure. Fig. 1 provides an overview of typical inbound and outbound flows at a warehouse. Generally, a facility has a large

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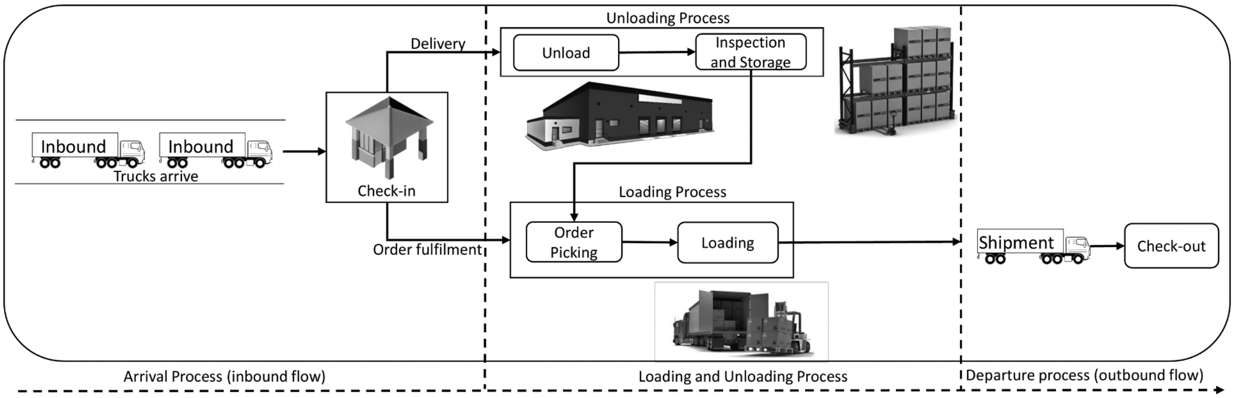


Fig. 1. Typical overview of warehouse operations.

volume of trucks, that are of different types (third-party carriers and company-owned trucks) and sizes (small, medium, and large), arriving at the site for goods delivery and/or pick-up.

When a truck enters the facility, it is usually processed at the check-in stage on a first-come-first-serve (FCFS) basis, where order information such as shipment number, truck weight, arrival time and carrier details are recorded. Depending on the volume of trucks arriving and sophistication of warehouse setting, the check-in operations are either conducted by a manual worker or automated technology system such as RFID (Radio Frequency Identification). Generally, the key performance indicators at the check-in are processing time, truck waiting time and queue length. Upon check-in, a truck delivering materials is routed to the receiving dock and a truck picking up finished goods is sent to the loading dock. Certain trucks may deliver and pick up goods, in which case it is first sent to the receiving dock followed by the loading dock. The receiving process involves inspection and storage of goods for future use, while the shipping process involves picking and loading the goods from the warehouse onto the trucks. Parameters such as loading/ unloading time, truck docking time, and number of available dock doors are important performance metrics of the receiving and shipping process. Finally, the shipment is ready for departure and the truck executes check-out operations. A common performance measure tracked among industry is the truck turnaround time (i.e., total time taken from arrival to check-out). In other words, the difference between the time at which vehicle, v, exited (or departed) the facility (D_v) and the time at which it arrived at the facility (A_v) is its turnaround time, $\tau_v = D_v - A_v$.

Inbound logistics is a vital step in warehouse receiving and shipping processes as it could have a direct impact on supply chain performance. Inefficient inbound operations could also lead to high annual detention fees - a major cost that companies endure in the warehousing sector, where a penalty is assessed by the carrier when the receiver holds the truck and driver beyond the agreed upon time (also referred to as 'free time'). In other words, to avoid detention fee, the truck turnaround time must be within the free time. Detention fees and free time are negotiable and differs depending on the carrier. A detention fee can vary from $15 to $90 per hour, while the free period is generally between 1 and 2 h. Long waiting time at check-in processes cut away the remaining free time, which the truck may spend loading/unloading, before a detention fee is assessed. This could result in a magnified impact on operation further downstream in the warehouse. Subsequently, internal warehouse capacity and resources may need to be shifted to load/ unload a truck whose free time is near expiration as a result of the time spent waiting in check-in lines. This may not always be possible due to low staffing levels or down equipment, thereby resulting in high detention fees paid to carriers.

The truck turnaround time increases mainly due to the delays at each stage of the receiving process [2]. Check-in delay is the first form of congestion that truckers encounter when entering a warehouse facility. The wait at check-in arises primarily during peak-hours when the arrival rate (i.e., number of truck arrivals per unit of time) swiftly exceeds the service rate (i.e., number of trucks that are processed into the facility per unit of time). Also, staff shortage and incomplete/incorrect information on inbound documents (e.g., purchase order) could also contribute to long queues at check-in. Besides, congestion at check-in can degrade the reliability and performance of internal warehouse operations as they are reliant on inbound trucks [3]. Moreover, prolonged idling of queuing trucks is not eco-friendly as it increases the concentration of carbon dioxide (CO_2), a primary contributor to climate change, in the atmosphere. Therefore, eliminating or reducing the line of trucks waiting to be checked-in to the facility would not only achieve substantial cost savings but also result in a comparatively sustainable process for operations further downstream.

This research is motivated by a real-life case study of one of the largest consumer goods companies in the United States, which has operations in over 50 markets and sell their products in over 150 countries. In 2016 alone, they paid approximately $1.65 million in detention fees to third-party carriers. A large percentage of this detention fee is determined by how long the truck waits to enter the facility. Currently, trucks spend substantially more time idling at the check-in queue (53.3 ± 20.8 min) than the loading/unloading operations (28.8 ± 22.5 min) inside the facility. As the company seeks to minimize unnecessary costs and expand into new markets, it is crucial to reduce the capital spent on detention fees. In this paper, we investigate different alternatives to improve the operational efficiency of the truck check-in process with the primary objective of minimizing the detention fees paid to the third-party carriers. Furthermore, we also examine alternative approaches to reduce CO_2 emissions and achieve a trade-off between environmental and economic objectives.

The remainder of the paper is structured as follows. A brief review of similar work in the literature along with the research gaps are presented in Section 2. Section 3 presents the research methodology, and Section 4 discusses the details of the case study. The development of the simulation model for the current process and proposed approaches are discussed in Sections 5 and 6, respectively. A detailed analysis of the results obtained from the simulation models and managerial implications are presented in Section 7. Finally, conclusions and future scope of research are discussed in Section 8.

2. Literature review

Extensive research has been done to improve the issue of check-in delays during inbound logistics. In particular, avoiding traffic congestion is a critical problem at container terminals due to the mass volume of goods arriving at seaports [5]. Therefore, a majority of the prior work addresses the inefficiencies associated with truck check-in for warehouses (or container freight stations) situated at port terminals. Since the inbound logistics operations are similar for warehouses positioned at the seaports and inland locations, we review the literature regarding marine terminal inbound operations as well. The strategies adopted by most of the previous research on improving truck check-in operations can be broadly classified into three categories – appointment-based arrivals (scheduling a truck to arrive within a particular time-window), off-peak arrivals (extending hours of operation and shifting a portion of truck arrivals from busy hours to non-busy hours), and dispatching rules (determining the order in which the vehicles waiting in a queue are processed). Therefore, this section reviews some of the notable works pertaining to these strategies.

Most of the previous studies propose appointment-based arrivals to reduce truck congestion during inbound logistics [2, 4–12]. Chen et al. [5] addressed the issue of long truck wait time at the gates of a container terminal by using vessel dependent time windows, where the trucks are scheduled to arrive during a specific time interval based on the group to which they are assigned. Their optimization model reduced the average waiting time of trucks from 106 min to 13 min at a port in China. Similarly, Zehendner and Feillet [10] proposed a mixed integer linear program model to reduce overall delays by designing a truck appointment system with respect to the facility's workload and handling capacity. The authors evaluated their model using real-life instances and observed a 14 min reduction in the average turnaround time. Azab and Eltawil [8] studied the receiving process using simulation models and found that the arrival time dramatically influences the truck turnaround time. Further, the authors concluded that shorter delays could be achieved by designing an appointment system. Huynh [11] developed a discrete-event simulation to examine the impact of an individual (different appointment time for each truck) and block (common appointment for a group of trucks) appointment systems on the truck waiting time and throughput. Their simulation results suggested that individual appointment systems perform better and improve the turnaround time by 44% [11]. While appointment-based arrivals have improved congestion in many cases, it may not be suitable for all system settings as its use and success are greatly dependent upon the operating policies of individual facilities [7]. For instance, an appointment-system may fail if facilities do not incorporate a dedicated lane to prioritize the scheduled truck arrivals. Likewise, the truck arrival must be synchronized with the internal warehouse operation to maximize the benefits of an appointment system [3].

Despite having appointment-based time-windows, most truckers typically arrive during busy hours due to various reasons such as periodic bans of trucks on roadways during specific hours/weekends and labor regulations on rest periods and overnight driving [4]. Therefore, some researchers have adapted the traditional appointment-based arrival system to include off-peak hour arrivals. Bentolila et al. [4] developed and implemented a “Good-Night Program” in which the trucks are scheduled to arrive during off-peak hours as part of a pilot study conducted at a facility in Israel. As a result of this initiative, a truck entering the facility during off-peak hours is processed 16–17 min faster compared to peak-hour processing. Chen et al. [6] investigated the impact of designing an appointment system with off-peak arrivals on the truck waiting time. The authors proposed a mathematical model to coordinate truck arrivals, and their analyses indicated a 33% reduction in waiting time when 4% of the truck arrivals were shifted to off-peak hours. While off-peak hour arrivals reduce the likelihood of congestion, they also have many issues which impede its implementation [3, 13]. Truckers may be reluctant to arrive during off-peak hours without an incentive strategy. Moreover, facilities incur additional cost (e.g., labor and overhead) for extended hours of operation.

Appointment system for scheduled arrivals during regular or off-peak hours may not be suitable for warehouses with a co-located manufacturing facility. This is mainly because most truck arrivals are based around production, which often causes truckers to show up at similar times to the location. Therefore, unlike the conventional strategy of using scheduled truck arrivals, some studies focus on adopting dispatching rules for improving warehouse logistics. For instance, Arora and Patel [13] used the data collected by logistics management software (travel times, processing times, etc.) as inputs to a stochastic model and identified the list of trucks that could be processed next based on several factors such as road capacity and the likelihood of capacity being available at the destination. Upon implementation, the operational costs decreased by 20% and resulted in lower emissions. While studies on dispatching rules are scarce for external warehouse operations, it is prevalent for improving the internal logistics based on automated guided vehicles (AGVs) [14–16]. One of the earliest proposed rules dispatches AGVs to the closest load pick-up location in the warehouse to minimize the total distance traveled [14]. Le-Anh and Koster [15] extended the traditional rule by developing dynamic dispatching rules to route the AGVs based on weighted sum score of vehicle travel distance and load waiting time. While these rules do not account for future tasks, Kim and Bae [16] developed static dispatching rules that route AGV's based on the location and time of the upcoming tasks. Their rule significantly reduced the warehouse operational delays compared to the traditional rule for all the warehouse settings evaluated [16].

We have identified the following four gaps from the literature review. First, most of the previous research focused on minimizing truck turnaround time by improving check-in operations. While high detention fee is a common problem among the warehousing industry, prior studies do not explicitly consider it as a critical performance metric. Second, most of the current research does not

account for different types of loading and unloading procedures observed in realistic settings such as live load (incoming trucks wait on-site to be loaded/unloaded at a dock door) and drop-and-hook (incoming trucks drop the trailer that they carry, and leave with another loaded trailer). Since these procedures substantially differ in their average service time, ignoring them in the model could lead to incorrect estimation of performance measures such as truck waiting time, turnaround time, and detention fees. Likewise, studies in the literature consider all the arriving trucks to be of the same size (or capacity). However, in reality, the truck size varies, and larger vehicles emit more greenhouse gas compared to smaller ones. Therefore, studies focusing on reducing carbon footprint during inbound logistics should consider truck size to develop realistic models. Finally, we observed that most of the studies adopted an FCFS queue discipline during the check-in process. However, this strategy might not alleviate the problem of high detention fee or long turnaround time. This is primarily because of the variation in service time for different loading/unloading procedures. Since the free time for all trucks is the same, a truck performing a drop-and-hook procedure can wait longer at the check-in without incurring a detention fee compared to a live loading truck. While prioritizing trucks using dispatching rules could alleviate these issues, it is not studied extensively for check-in operations.

This research addresses these four gaps in the literature pertaining to truck congestion during inbound logistics. In this paper, we aim to improve the check-in process at a warehouse with co-located manufacturing facility such that the annual detention fee and carbon emissions are minimized. We incorporate realistic settings (such as varying truck size and different loading/unloading procedures) in our modeling approach and propose novel dispatching rules that are generic and can be adopted by any facility characterized by long waiting time for check-in and high detention fees. Table 1 provides a summary of the recent relevant literature and highlights the contributions of this research.

3. Methodology

This paper focuses on the research stream dealing with the problem of long waiting time at the check-in stage of the warehouse receiving process. We adopt the well-established data-driven process improvement methodology that constitutes five phases: Define, Measure, Analyze, Improve, and Control (DMAIC). In the *Define* phase, the system is observed and its process is mapped onto a flow chart for logical understanding of the sequence of events. This phase also establishes the current challenges and research objectives. The *Measure* phase involves the collection and pre-processing of historical data. It provides a descriptive summary and better understanding of the current system measures such as average truck arrivals per hour, average waiting time, and annual detention fee. The *Analyze* phase fits the historical data to statistical distributions and involves the development of a Baseline model to understand and visualize the current inbound operations. In this research, we resort to the use of discrete-event simulation to model the current operations because it has been widely adopted to solve problems throughout the supply chain logistics industry and has become a viable tool for decision makers [2,8,12,17–20]. Note that the simulation model uses the fitted distribution as input parameters and is designed based on the process map established in the earlier phase. Upon verifying and validating the Baseline simulation model, it is observed for areas of improvement with respect to the performance measure(s) of interest. Subsequently, potential alternative models are designed, developed and evaluated in the *Improve* phase. In addition, the performance of the alternative scenarios is statistically compared to the current operations. Finally, the *Control* phase consists of estimating the expected cost, savings, ease of implementation, and resource utilization. During the last two phases, it is important to document and visualize all results. Note that the DMAIC methodology is generic and can be used when a process improvement strategy should be investigated by comparing an existing configuration to alternative scenarios [21].

4. Case study

We consider a real-life case study of a consumer goods company and study their inbound logistics at a warehouse for improving the check-in. Further, we follow the DMAIC framework discussed in Section 3 to analyze and improve the current process and performance systematically. While this case study is specific to the site under study, the applied methodology and potential solution scenarios are generalizable. Therefore, it may easily be tailored to different facility requirements, thereby allowing this research methodology and proposed alternatives to be applicable for industries experiencing truck congestion during inbound check-in and paying high detention fees.

4.1. System description

The consumer goods company under study operates more than ten central manufacturing locations (each manufacturing site has a warehouse attached), where the products are manufactured and distributed within the United States. In this paper, we chose one of the warehouse facilities located in the southern region of the United States for two dominant reasons – (i) unlike other sites, this location processes around 10% more loads per week and (ii) the company has received complaints from the city government due to the trucks queueing onto the public roads, creating traffic congestion for city residents.

The chosen facility (as shown in Fig. 2) operates for 24 h a day (3 shifts of 8 h each) and 7 days a week. On average, around 2800 trucks enter the facility in a week through one of the two entrances (main and secondary). These trucks are broadly classified into four types (A, B, C, and D) depending on their characteristics such as truck ownership and consumer needs. Truck type A is a fleet owned by the company and carries the finished product within a 250-mile radius. Truck type B carries raw materials into the facility for production needs, which are unloaded at the warehouse for storage. Truck types C and D transport finished goods from the warehouse to the retailers. The company owned trucks and trucks carrying raw materials enter the facility through the secondary

Table 1
Summary of recent relevant literature.

Author (Year)	Objective Turnaround Time	Emissions	Waiting Time	Detention Fee	Solution Strategy Scheduled Arrivals	Dispatching Rules	Modeling Approach Discrete Event Simulation	Optimization Model	Model Parameters Truck Size	Loading/ Unloading Procedures	FCFS Queue Discipline	Priority Queues for Check-in
Arora and Patel (2008)		✓	✓			✓		✓				✓
Huynh (2009)	✓				✓		✓					✓
Kiani et al. (2010)			✓		✓		✓				✓	
Chen et al. (2012)			✓		✓			✓			✓	
Chen et al. (2013)		✓	✓		✓			✓	✓		✓	
Zehendner and Feillet (2014)	✓		✓		✓			✓			✓	
Azab and Eltawil (2016)	✓				✓		✓				✓	
Zhou et al. (2018)	✓				✓		✓	✓			✓	✓
Li et al. (2018)		✓	✓		✓		✓				✓	✓
This Research		✓		✓		✓	✓		✓	✓	✓	✓

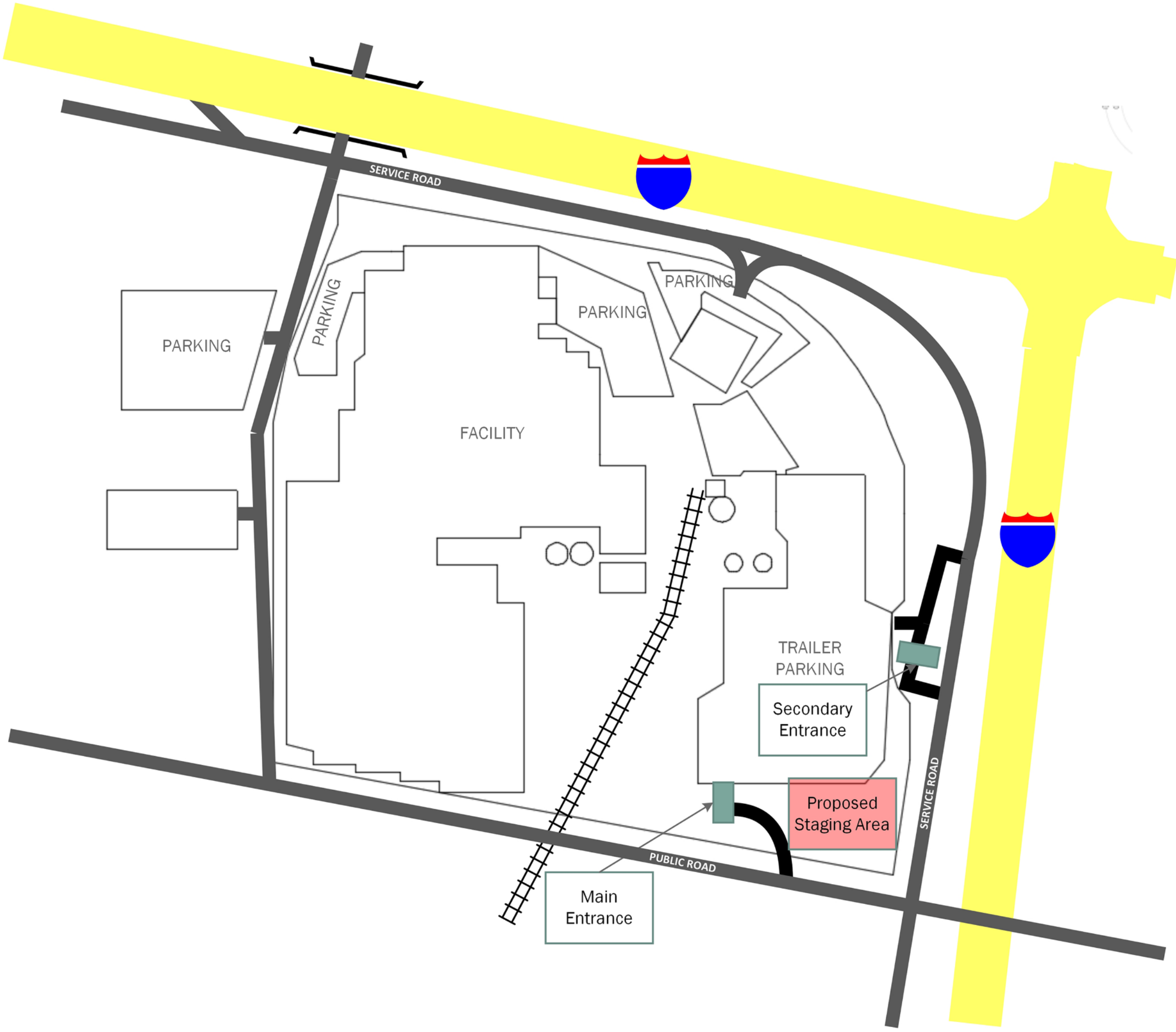


Fig. 2. Layout of the facility under study.

entrance, and trucks that carry finished goods (types C and D) arrive through the main entrance. Upon entering, they perform a live load or drop-and-hook loading/unloading procedure. In the case of drop-and-hook procedure, the loaded trailers are moved to the yard by a spotting service (smaller tractors that stay on site and are committed to moving loaded/unloaded trailers) and are ready for pick-up prior to a truck's arrival. Each truck type may vary in size as small (S), medium (M) and large (L) trucks, depending on the shipment destination and customer. For example, heavier loads or shipments traveling longer distances will require large trucks. Table 2 provides a summary of the truck characteristics for each truck type.

The long waiting lines to enter the facility forces the company to pay high detention fees to the third-party carriers. Besides, the facility is also facing a backlash from the local government due to the truck queue overflowing from the main entrance onto the city road causing unnecessary traffic congestion to the residents. Unless corrective action is taken immediately, the city government will start imposing fines for interfering with local traffic. Moreover, trucks idling due to long waiting times is not sustainable as it emits carbon dioxide (CO_2), which are known to have harmful effects on humans and the environment. As trade continues to grow, the

Table 2
Truck types and their characteristics.

Truck type	Assigned entrance	Ownership	Loading/Unloading procedure	Average dwell time (mins)	Truck size		
					S	M	L
A	Secondary	Company-owned	Drop and Hook	10	0%	0%	100%
B	Secondary	Third-party carrier	Drop & Hook/Live Load	15	25%	0%	75%
C	Main	Third-party carrier	Drop and Hook	30	25%	25%	50%
D	Main	Third-party carrier	Live Load	60	0%	50%	50%

spotlight has been on fuel and environmentally friendly transportation solutions. Also, companies who successfully implement environmentally friendly logistics solutions generate a lot of positive press coverage. For these reasons, the company under study is not only interested in minimizing the detention fee paid to the carrier, but also in reducing the carbon footprint emitted from the trucks.

4.2. Sequence of events

A process map of current state operations (Fig. 3) enabled an easier study of the entire check-in process by mapping the interconnection of sub-processes to understand the flow throughout the system. The flow is similar to the typical receiving process illustrated in Fig. 1 but has certain unique characteristics with respect to truck flow and site layout. Each truck that arrives at the facility has a certain process.

Truck types C and D enter through the main entrance, which has two lanes with space for two trucks at the check-in shack. However, only one truck is processed at a time due to the presence of one check-in server. The trucks waiting to be processed into the facility must wait in the queue connecting to the main entrance and public road (as shown in Fig. 2). The queue at the main entrance can accommodate seven trucks, beyond which the queue reaches the city roads. Truck types A and B enter through the secondary entrance, which has a single lane allowing only one truck to check-in at a time. Further, the secondary entrance is unmanned and uses RFID technology for automatic and faster check-in processing. Nevertheless, the RFID technology may fail to recognize the RFID-tags in some trucks, thereby disrupting the check-in process at the secondary entrance. In such situations, those trucks are re-routed to the main entrance through the service road for manual check-in into the facility. Following check-in at the main and secondary entrances, trucks proceed to load/unload material, either by drop and hook or live load procedure. Finally, the trucks leave the facility, and the total time spent in the system is recorded to determine whether a detention fee should be paid to the third-party carriers.

4.3. Data collection and analysis

In order to determine the arrival and service time distribution for use in the simulation model, nine weeks of data were extracted from the warehouse management system and included a total of 24,901 trucks going through the check-in process at the facility. The data is pre-processed to identify outliers, inconsistencies and missing values, and then analyzed to determine the parameters for the simulation model. The first three days of the work week (Monday, Tuesday, and Wednesday) were found to be the busiest and appeared to follow similar arrival rate patterns. Therefore, a Kruskal–Wallis (K-W) test, was conducted to assess the homogeneity of the arrival rates of the three busy days. The K-W test confirmed that the hourly arrival data for busy days could be combined into a single dataset for distribution fitting. The chi-square test (at $\alpha = 0.05$) is used to identify the theoretical distribution that fits well to the observed data. The test results indicate a Poisson distribution with a time-varying arrival rate to be a good fit for modeling truck arrivals (p-value > 0.05). A plot of the total hourly arrival rates by each truck type for a typical busy day is shown in Fig. 4. However, the trucks arriving on the least crowded days (Thursday-Sunday) very rarely incurred detention fee (or exceeded their free time). In other words, during the least crowded days, the queue length is very small such that the trucks do not experience high wait times nor spillover to the city roads.

Since the check-in processing time data is not available, a time study was conducted at the site to obtain an estimate of the main and secondary entrances processing times. The time study was implemented by recording the time when the truck initially stops at the check-in station, until the truck starts proceeding into the facility. The snapback timing method, where the stopwatch is reset to zero at the start of each work element, was adopted to record the processing time. The study was conducted across five days and two different shifts in order to capture worker variability due to a single operator working at the facility on a given shift. In total, 25 samples were observed per shift, resulting in 250 data points collected over the time period. On analyzing the service time data, the average values are estimated as 3.75 (min: 3.25 and max: 4.00) minutes at the main entrance and 0.5 (min: 0.25 and max: 0.75) minutes at the secondary entrance. The service times were also verified with facility managers who deal with the process on a daily basis. Therefore, the service time is modeled as a triangular distribution based on the observed values. Lastly, the probability of RFID check-in failure at the secondary entrance was calculated as 48% by examining the proportion of trucks that enter the facility through the main entrance.

5. Discrete event simulation

5.1. Model development

The current operations (baseline model) of the test site was developed using Simio® simulation software, which adopts the conceptual logic illustrated in Fig. 3. To generate a visually realistic simulation model that is to scale, a map overview from Google Earth was used to trace over the landmarks and travel paths on the site. The hourly arrival rate parameters, check-in processing time and loading/unloading distributions fitted based on historical data were used in model development. These parameters are easily adjustable allowing for the simulation model to be scaled across multiple sites and industries. Truck sizes are sampled from a discrete probability distribution each time an entity is created based upon the proportions given in Table 4. In other words, when a truck of a specified type is generated, it has a probability of being small, medium, or large. The simulation and system components are summarized in Table 3. Even though the model was developed to reflect the operations realistically, it becomes impossible to exactly replicate a real system due to complex interactions and human behaviors. Therefore, the following reasonable assumptions were used to construct the simulation model.

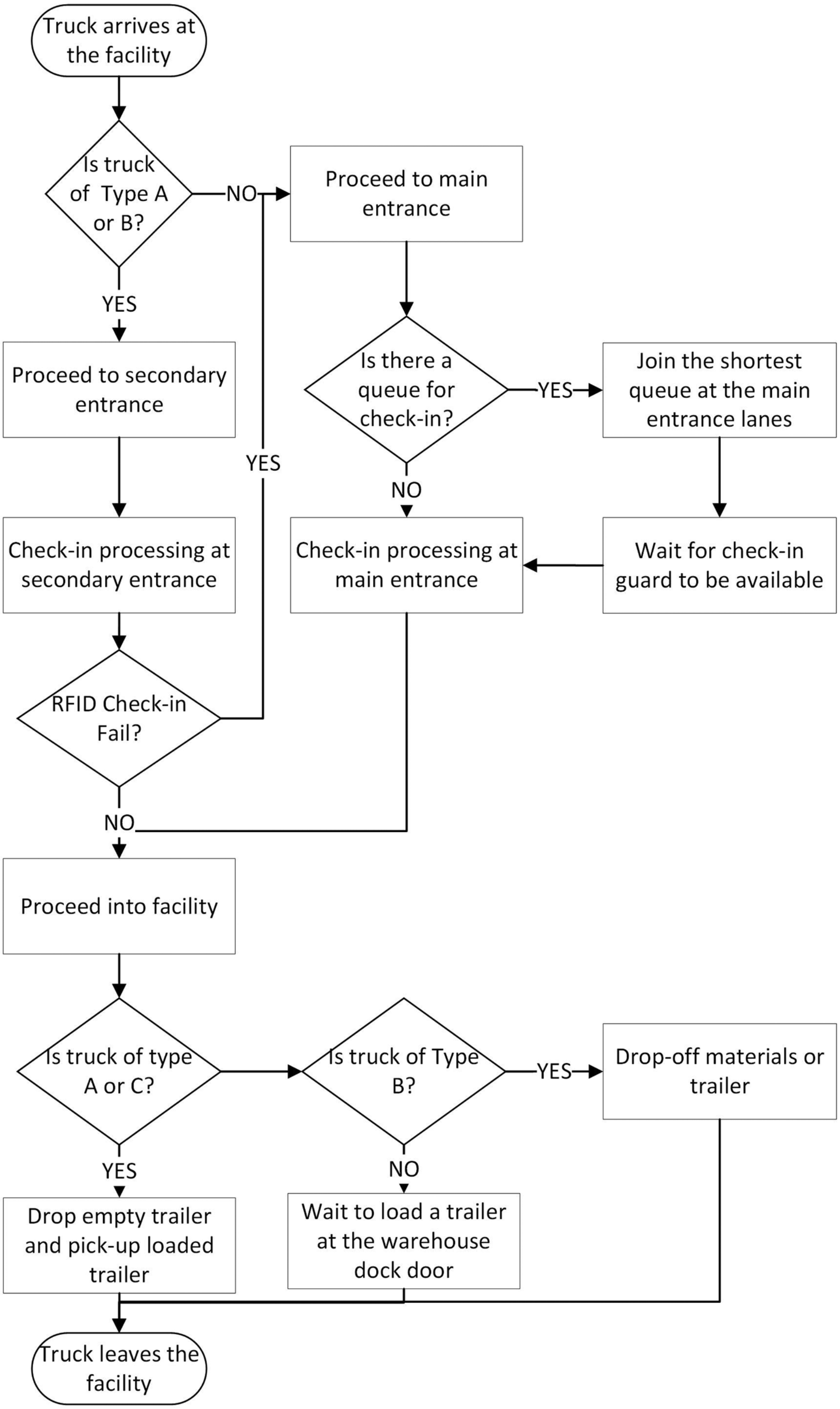


Fig. 3. Process map of the current operations.

- Travel times (speed limits, acceleration, and deceleration of trucks) are the same for all the truck types
- Trucks do not balk (i.e., leaving the system after being notified that they will have to wait in queue) or renege (i.e., leaving the system after waiting in the queue for a duration of time) due to waiting time
- A worker is always available at the main entrance to facilitate check-in

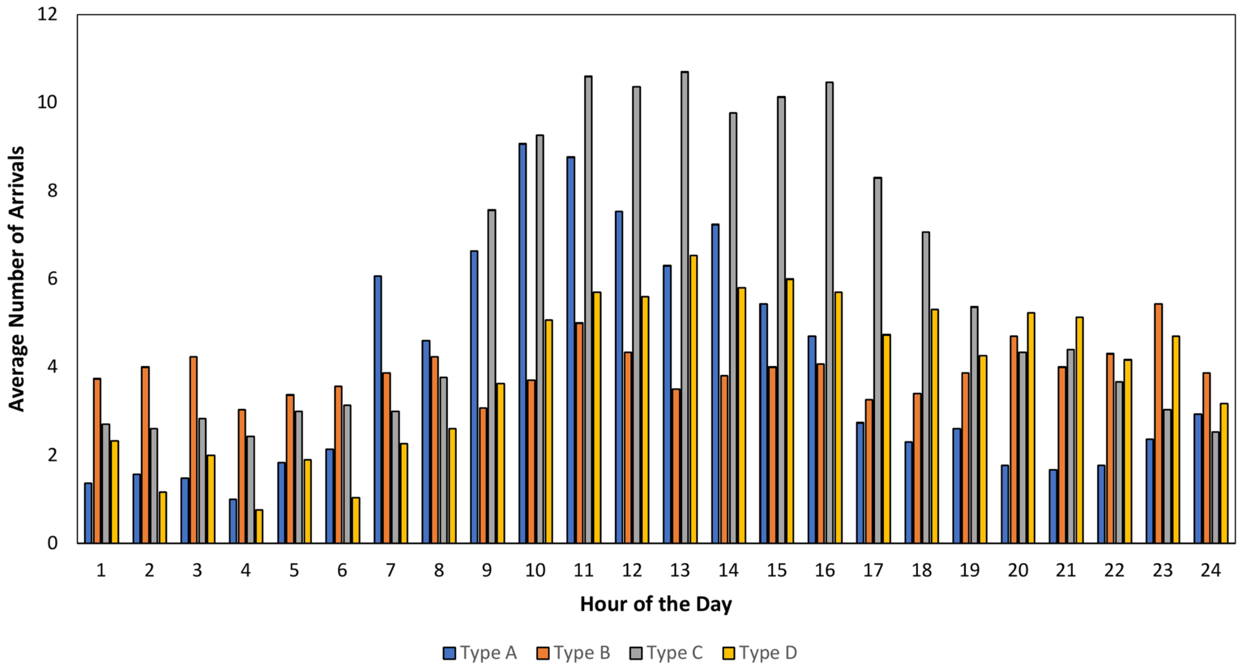


Fig. 4. Hourly arrival rates by truck type for a typical day.

Table 3
Simulation model and actual system components.

Simulation components	System components
Entity	Truck
System type	Terminating
Attributes	Truck type, truck size, CO_2 emission rate
Events	Truck arrival, truck check-in completion, etc.
Resources	Check-in guards
Inputs	Truck hourly arrival rates, check-in processing time
Outputs	Annual Detention Fee, Annual CO_2 emissions

- There is no restriction on the queue length at the entrances

Even though the facility operates for 24 h, the company faced the problem of truck congestion and check-in delays only during peak hours (10 am–5 pm), when 49% of the inbound arrivals occurred. Therefore, the check-in process is modeled as a terminating simulation, where the model is run for 10 h (8 am–5 pm) with a two-hour warm-up period (excluded from output analysis). Since the peak hour arrivals were homogenous for different days of the week, the results for a typical busy day are valid and representative of all the busy days experienced by the facility. Therefore, the simulation model was run for a single day with 100 replications. Further, it is assumed that if the system can process the volume of trucks arriving during the busiest days of the week, then it can handle all subsequent days with fewer amounts of truck arrivals. Table 4 summarizes the key input parameters of the simulation model.

5.2. Model verification and validation

After constructing a model, it is important to both verify and validate it for accuracy. Since the simulation model has different complexities such as multiple truck types, different truck sizes and unique flow for each truck type, we adopted a combination of different methods to verify the model. Fig. 5 provides a snapshot of the baseline model. We used different colors to differentiate the truck types and verified their flow in the simulation model by running it in step mode, where the model is paused after every event instead of running continuously. Also, user-defined conditions were programmed into the simulation model to flag any anomalous behavior (events). This allowed easy verification for complex processes and ensured entities have the correct attributes throughout the simulation run such as truck types traveling to right destinations and having appropriate docking time and CO_2 emissions attributes. Finally, the model was verified by the facility employees and managers, who are experts on the process and have extensive simulation knowledge.

Table 4
Arrival and service time distributions.

Parameter	Value
Number of Arrivals	
• 10 am – 11 am	Poisson ~ (27.10)
• 11 am – 12 pm	Poisson ~ (30.06)
• 12 pm – 1 pm	Poisson ~ (27.83)
• 1 pm – 2 pm	Poisson ~ (27.03)
• 2 pm – 3 pm	Poisson ~ (26.60)
• 3 pm – 4 pm	Poisson ~ (25.56)
• 4 pm – 5 pm	Poisson ~ (24.93)
Proportion of Trucks (Small, Medium, Large)	
• Truck Type A	(0.00%, 0.00%, 22.15%)
• Truck Type B	(5.54%, 0.00%, 16.64%)
• Truck Type C	(8.32%, 8.32%, 16.65%)
• Truck Type D	(0.00%, 11.19%, 11.19%)
Check-in Processing Time	
• Main Entrance (minutes)	Triangular ~ (3.50, 3.75, 4.00)
• Secondary Entrance (minutes)	Triangular ~ (0.25, 0.50, 0.75)

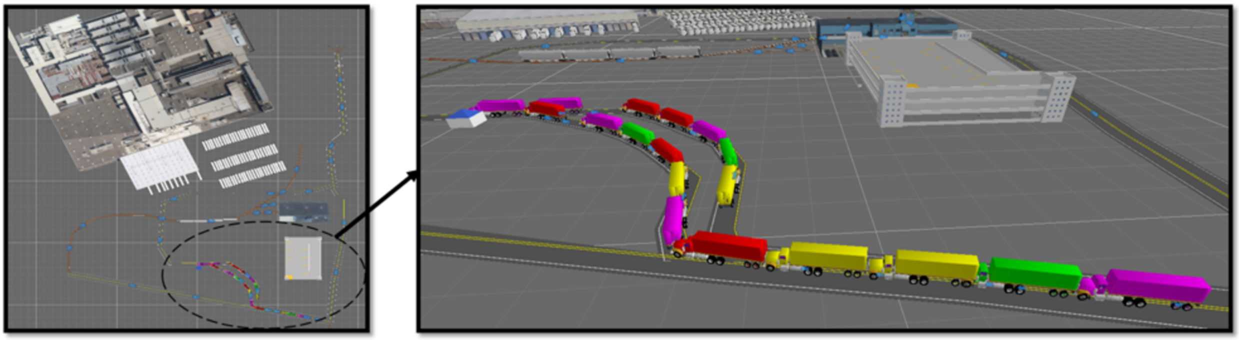


Fig. 5. Snapshot of the simulation model for the current operations.

Before evaluating the results and different what-if scenarios, the baseline model was calibrated so that its behavior would accurately resemble the current operation of the actual system. The model was validated for the following measures, namely, total truck arrivals and average waiting time at the main entrance. A t-test (at $\alpha = 0.05$) was conducted to validate these measures and Table 5 summarizes the results of the statistical test. The p-value for all truck types against both measures is greater than 0.05, confirming that the simulation model is not statistically different from the actual system.

6. Alternative scenarios

The current operations are analyzed for improvements by evaluating feasible options that take into account the technological requirements. The scenarios are designed for two situations – (i) utilizing current facility resources more efficiently, (ii) procuring new state-of-the-art equipment. Furthermore, the proposed scenarios are generic, allowing any facility or company to adapt and apply similar procedures easily.

6.1. Scenario 1 – impact of staging area with FIFO sequencing

Scenario 1 considers the use of a company-owned land near the main entrance as a staging area for the vehicles entering the facility. In this setting, all the trucks arriving at the facility will wait at the staging area if the queue at the main entrance is full.

Table 5
Validation of key measures in the model.

Truck type	Truck arrivals (trucks/hr) Simulation model	Actual data	p-value	Waiting time (mins) Simulation model	Actual data	p-value
A	42.69	43.3	0.32	33.6	35.5	0.113
B	27.96	27.86	0.85	0.180	0.165	0.137
C	70.33	68.91	0.125	61.8	58	0.163
D	40.06	39.04	0.223	62.4	66	0.188

Further, the trucks are dispatched on a first come first serve (FCFS) basis from the staging area. While this scenario is not expected to substantially improve/worsen the detention fee paid to the carriers, it will alleviate the spillover of trucks onto the public road. Thus, this arrangement would resolve the congestion complaints from the residents and avoid any penalty from the city government.

6.2. Scenario 2 – single attribute dynamic dispatching rule at staging

Scenario 2 considers the use of a dispatching rule to prioritize trucks at the staging area. Since detention fees are assessed by carriers only when their trucks stay on-site longer than the agreed upon free period, we use their remaining free time at the staging area as an attribute to prioritize the vehicles entering the facility. As shown in Eq. (1), the remaining free time of vehicle v, R_v^F, at the staging area is estimated as the difference between the contractual free time (T_v^F) and the time spent waiting in the staging area (T_v^S). A score for each vehicle (S_v) is then computed as the difference between the remaining free time (R_v^F) and expected loading/unloading time of that vehicle (μ_v^D) inside the facility (Eq. (2)). Moreover, the scores are continuously updated in real-time for all the trucks in the staging area. Thus, the score reflects the average amount of time a truck can spend in the staging area before it will start incurring a detention fee. If the queue at the main entrance can accommodate another vehicle, then the truck with the smallest score is released first from the staging area for check-in.

$$R_v^F = T_v^F - T_v^S \tag{1}$$

$$S_v = (R_v^F - \mu_v^D) \tag{2}$$

We present the following numerical example to illustrate the proposed dispatching rule (Scenario 2). Consider a situation in which there are two trucks in the staging area. Further, Trucks 1 and 2 arrived at the staging area at 10:00 am and 10:05 am, respectively. Both the trucks have 120 min of free time (i.e., $T_1^F = T_2^F = 120$). However, Truck 1 is expected to take an average of 30 min ($\mu_1^D = 30$) for loading/unloading operation inside the facility, while Truck 2 is expected to take 60 min ($\mu_2^D = 60$). At 10:10 am, the time spent in the staging area for Truck 1 is 10 min and Truck 2 is 5 min. In other words, the remaining free time for Truck 1 (R_1^F) is 110 min and Truck 2 (R_2^F) is 115 min. To determine the truck that must be dispatched next, we compute the score for each vehicle (S_1 and S_2), which reflects the average amount of time that a truck can spend in the staging area before it will start incurring a detention fee. In this case, Truck 1 can spend about 80 min ($S_1 = 110 - 30$) and Truck 2 can wait 55 min ($S_2 = 115 - 60$) in the staging area before a detention fee is assessed. Since the truck with the smallest score is released first, Truck 2, which arrived last is actually processed first in this situation.

6.3. Scenario 3 – multi-attribute dynamic dispatching rule at staging

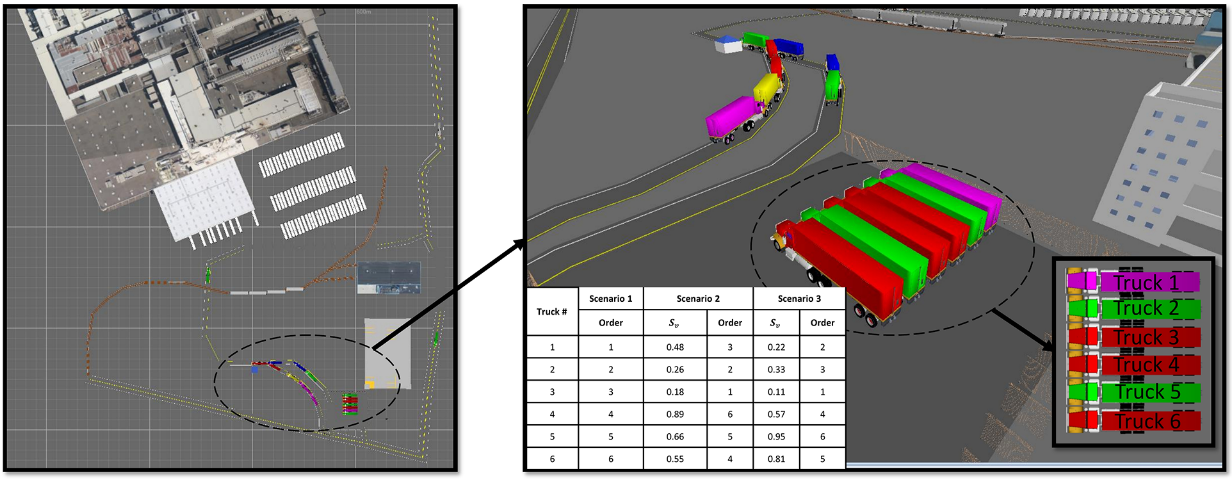
As companies are at the forefront of creating a sustainable future, the interest in developing green logistics has increased substantially over the last decade. Scenario 3 seeks to extend the single attribute dispatching rule to include the impact of carbon footprint of trucks waiting to enter the facility. The rate of CO_2 emission (C_v) during idling of trucks at the staging area varies depending on the truck size (small, medium, and large). Hence, a dispatching rule with two attributes (remaining free time and carbon footprint) is proposed as shown in Eq. (3), where w_1 and w_2 are the relative importance of each attribute. The first term in the equation, ($R_v^F - \mu_v^D$), determines the time after which a detention fee will be assessed for that truck, while the second term ($T_v^S \times C_v$) provides the average CO_2 emitted by that truck. Thus, Scenario 3 attempts to achieve a trade-off between the detention fees paid to carriers and CO_2 emission from the trucks. Since it is a bi-criteria model, different weights can be assessed for each criterion depending on the interest of the decision maker. In other words, it is possible to achieve a deeply optimized environment for either detention fee or CO_2 by assigning the parameter of interest a weight of one, and the other parameter a weight of zero. However, to achieve cost savings to the company, it is expected that more importance will be given to minimizing detention fee (i.e., $w_1 > w_2$). The scores are updated in real-time and the vehicle with the smallest score is dispatched first from the staging area upon available capacity.

$$S_v = w_1(R_v^F - \mu_v^D) - w_2(T_v^S \times C_v) \tag{3}$$

Fig. 6 illustrates the dispatching order of trucks for Scenarios 1 – 3 at a particular time instance. It can be observed that the trucks are indexed from 1 to 6 according to their order of arrival along with the score for each truck (S_v) in the staging area for Scenarios 2 and 3. Note that Eqs. (2) and (3) are integrated into the model using Simio® simulation software and is utilized to derive the values of S_v (shown in Fig. 6) for Scenarios 2 and 3, respectively. Further, the simulation model updates the scores dynamically as the state of the system changes. Hence, the dispatching order observed is for a particular instant and will continuously change over time. Since Scenario 1 operates under a FCFS dispatching rule, a score is not necessary to determine the processing order.

6.4. Scenario 4 – impact of automated and faster check-in process

Scenario 4 investigates the impact of procuring and implementing an automated check-in kiosk at the main entrance, which will substantially reduce its check-in processing time. The installation of automated kiosks will allow the truck drivers to self-check-in to the facility while staying in the cab of the truck. Further, this approach will also eliminate the need for a full-time check-in guard at the main entrance. However, the shift-manager is still required to assist in the routing of trucks once they enter the facility. Therefore, implementation of this scenario will fully automate the check-in process at the facility, where the main entrance adopts the



Truck #	Scenario 1	Scenario 2		Scenario 3	
	Order	S_v	Order	S_v	Order
1	1	0.48	3	0.22	2
2	2	0.26	2	0.33	3
3	3	0.18	1	0.11	1
4	4	0.89	6	0.57	4
5	5	0.66	5	0.95	6
6	6	0.55	4	0.81	5

Fig. 6. Snapshot of the simulation model for the proposed alternatives with staging area.

automated kiosk and the secondary entrance uses the current RFID technology. However, truck types C & D are still required to enter through the main entrance. This is because a carrier must purchase company and site-specific RFID tags for their trucks to be processed through the secondary entrance. Due to the nature of the trucking industry, a particular truck may only pick up a single load from that facility on a monthly or yearly basis. In other words, transporters do not send the same truck to the facility every time an order is delivered or picked-up. As a result, they must invest in site-specific RFID tags for all their fleet of trucks so that it could be processed at the secondary entrance. Considering the additional capital investment and infrequent visits per truck, it would be difficult to convince the carriers to adopt RFID technology.

6.5. *Performance measures*

Models are evaluated by comparing the measures of annual detention fee and annual carbon footprint emittance for 100 replications. For each scenario (k), the detention fee and CO_2 emission are estimated using the total time spent by each truck in the system, which is the difference between the truck departure time (D_v) from the facility and arrival time to the facility (A_v). Therefore, if the total time in the system exceeds the contractual free time (T_v^F), then a detention fee (η per hour) is incurred. Otherwise, the company does not pay any fee for that truck. Similarly, the total CO_2 emission of a truck is the product of the rate of CO_2 emission per hour and the total time spent by that truck at the facility. The detention fee and CO_2 emission of each truck is calculated using Eqs. (4) and (5), respectively.

$$P_v = \max\{0,\ (D_v - A_v - T_v^F)\ \times \eta\} \tag{4}$$

$$E_v = C_v \times (D_v - A_v) \tag{5}$$

The greatest proportion of detention fee occurs on the busiest days of the week - Monday, Tuesday, and Wednesday. Annual penalty or detention fee ($\bar{P}$) and CO_2 emissions ($\bar{E}$) are calculated by taking the average daily amount and multiplying the quantity by three busy days per week and 50 annual working weeks in the year. Note that the trucks arriving during the non-busy days did not lead to a meaningful increase in annual detention fee at the facility as discussed in Section 4.3. Therefore, we did not consider the least busy days in the estimation of the performance measures. However, if the queue during non-busy periods increases, then the proposed alternatives are still valid and the results can be extended to the remaining days by incorporating their arrival patterns in the simulation model.

7. Experimental results

This section presents the results of the baseline scenario and alternatives described in Sections 5 and 6, respectively. For the multi-attribute dispatching rule (Scenario 3), the importance associated with the detention fee (w_1) is set to 0.75 and the weight for minimizing CO_2 emission (w_2) is set to 0.25. A detention fee of $70 per hour is assessed by the third-party carriers. Further, the CO_2 emission rate is estimated at 5332 g/hr, 8887 g/hr and 13,331 g/hr for small, medium and large trucks, respectively [22].

The simulation results of the baseline model indicate the average and maximum queue length to be 17.04 trucks and 28.38 trucks, respectively. Further, the queue extends beyond the curved road at the main entrance and leads to the city road 80% of the time. As expected, all the proposed scenarios avoided the queue length to spillover to the city road either by using the staging area or automated kiosk.

Table 6 presents the average and standard deviation of waiting time of each truck type across all scenarios. As a result of faster check-in processing at the secondary entrance, the waiting time of trucks entering through that entrance is substantially lower

Table 6
Average waiting time and standard deviation (in minutes) of different truck types across all scenarios.

Truck type	Average waiting time (SD) Baseline model	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Type A	33.6 (10.8)	34.8 (10.8)	31.2 (12.6)	38.4 (10.8)	10.2 (0.84)
Type B	4.8 (0.05)	4.8 (0.02)	4.8 (0.03)	4.8 (0.02)	4.8 (0.02)
Type C	61.8 (21.6)	62.4 (21.0)	44.8 (22.8)	48.6 (23.4)	9.6 (0.84)
Type D	62.4 (21.0)	63.0 (21.0)	32.6 (16.8)	38.6 (18.0)	9.6 (0.84)

compared to the trucks entering via the main entrance. Even though truck types A and B enter through the secondary entrance, the former had a substantially higher waiting time. This is because the company-owned trucks had old RFID tags resulting in high check-in failure at the secondary entrance, which in turn forced these trucks to be rerouted to the back of the main entrance queue. However, type B trucks are all equipped with new expensive tags and hence the RFID check-in never failed.

A Tukey's multiple comparison test (at $\alpha = 0.05$) was conducted to test the statistical significance of the average waiting times presented in Table 6. The statistical testing results indicate that the average waiting times of truck types C and D in Scenarios 2 – 4 are significantly better than the waiting time in the current system. Also, the average waiting time for all truck types in the baseline model is not significantly different from the waiting time values in Scenario 1. Therefore, adding the staging area at main entrance and dispatching the trucks on FCFS basis eliminates the truck spillover to the city roads without significantly increasing the waiting times. Besides, the average waiting time of type B trucks entering through the secondary entrance did not change significantly across scenarios as the proposed alternatives are focused on improving the congestion only at the main entrance. While the average waiting times of truck type A in the baseline model is not significantly different from the waiting time values in Scenarios 1–3, it is significantly better under Scenario 4 as automation at main entrance reduced the waiting time of the rerouted type A trucks.

Based on the total time spent in the system, Fig. 7 provides the average proportion of trucks that exceeded their contractual free time of two hours in the facility. Note that truck type B never exceeded their contractual free time and truck type A does not have a contractual free time as it is company-owned. It can be observed from Fig. 7 that over 38% of trucks in the baseline model exceeded their contractual free time and paid detention fees. Prioritizing trucks based on their loading/unloading times (Scenarios 2 and 3) reduced the proportion of trucks violating the contractual agreement by 27% and 17%, respectively. Also, Scenario 4 drastically improved the truck turnaround time and eliminated the proportion of trucks that spend more than 2 h in the facility.

The estimated annual detention fee and the CO_2 emission for the current system ($\bar{P}_B$ and $\bar{E}_B$) and the proposed alternatives ($\bar{P}_k$ and $\bar{E}_k$, $k = 1, 2, 3, 4$) along with the percentage difference from the baseline model are presented in Table 7. The percentage difference between the detention fee in the baseline model and scenario k (fee_gap_k) is calculated using Eq. (6). Similarly, the percentage difference from baseline emission (emission_gap_k) is calculated using Eq. (7).

$$\mathbf{fee\_gap}_k = \left(\frac{\bar{P}_B - \bar{P}_k}{\bar{P}_B}\right) \times 100, \quad \boldsymbol{k} = 1, 2, 3, 4 \tag{6}$$

$$\mathbf{emission\_gap}_k = \left(\frac{\bar{E}_B - \bar{E}_k}{\bar{E}_B}\right) \times 100, \quad \boldsymbol{k} = 1, 2, 3, 4 \tag{7}$$

Even though Scenario 1 eliminates the queue spillover, it results in higher detention fee and CO_2 emission compared to the Baseline model. This is expected because Scenario 1 adopts a very minimal process change, where each truck is routed to the staging

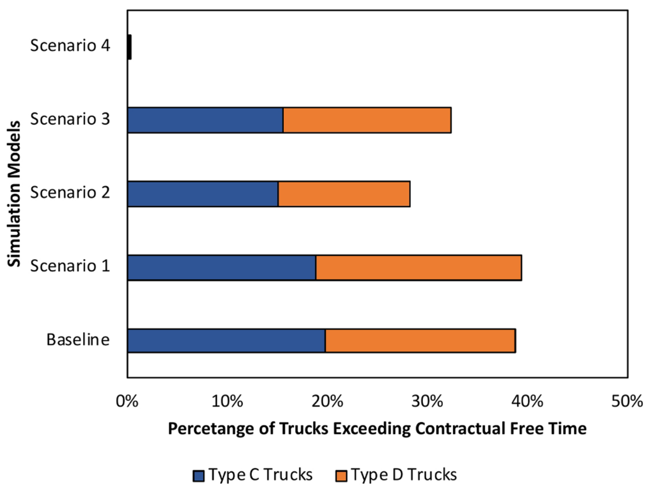


Fig. 7. Truck check-in efficiency with respect to contractual free time.

Table 7
Estimated detention fee and CO_2 emission of models.

Scenarios	Annual detention fee ($/year)	fee_gap_k	Annual CO_2 emission (ton/year)	$emission\_gap_k$
Baseline	76,751.16	–	219.13	–
Scenario 1	79,361.39	−3.40%	221.89	−1.26%
Scenario 2	34,231.20	55.40%	203.53	7.12%
Scenario 3	51,458.97	32.95%	175.03	20.13%
Scenario 4	0.00	100.00%	42.56	80.58%

area before driving to the main entrance. As a result of the additional step in the existing process, the trucks are expected to spend more time in the system resulting in a slightly higher detention fee and carbon footprint. However, Alternatives 2 – 4 performed substantially better than the baseline model with respect to detention fee savings. Moreover, the adoption of automated check-in kiosks (Scenario 4) dominates all the models with respect to detention fee savings and reduction in CO_2 emissions. However, it may not be economical as it requires strategic process redesign and cross-training employees. Compared to the current process, the single attribute dispatching rule (Scenario 2) achieves over 55% cost savings and 7% reduction in carbon footprint. On the other hand, the multi-attribute dispatching rule reduces the detention fee by 33% and CO_2 emission by 20% compared to the Baseline model. Since the two-attribute model aims to achieve a trade-off between detention fee and CO_2 emission, the cost savings are not as high as Scenario 2 which focuses only on minimizing the detention fee. Fig. 8 shows the impact of varying the weights associated with the two-attributes from 0 to 1 for Scenario 3. It can be observed that the detention fee increases dramatically when more emphasis is placed on minimizing carbon footprint (i.e., when $w_2 \rightarrow 1$). Likewise, the emission is high when the scenario is deeply optimized to reduce detention fee (i.e., when $w_1 \rightarrow 1$). Thus, it allows the decision-makers to decide on a trade-off between the performance measures, and choose appropriate weights for Scenario 3.

7.1. Impact of service time variation

In the initial analysis, the average service time at the main entrance is assumed to follow a triangular distribution with a mean of 3.75 min, minimum of 3.5 and maximum of 4 min. On the other hand, the RFID technology at the secondary entrance has a faster service time with a mean of 30 s and standard deviation of 2 s. To test the impact of service time variation on detention fee and CO_2 emission, the minimum and maximum values of the triangular distribution is varied, while fixing the mean to be constant. Fig. 9 shows the impact of service time variation on detention fee and carbon footprint.

Consistent with the previous analysis, Alternatives 2–4 have substantially lower detention fee compared to the current check-in process even when the service time variation is increased. Likewise, in comparison to the baseline model, the CO_2 emission is considerably improved in Scenarios 2–4 for all values of service time variation. Further, it can be observed that the increase in service time uncertainty increases both the performance measures in all scenarios except Scenario 4. This is because an increase in service time uncertainty may increase the average queue length at the main entrance (or average truck waiting time), which subsequently worsens the performance measures.

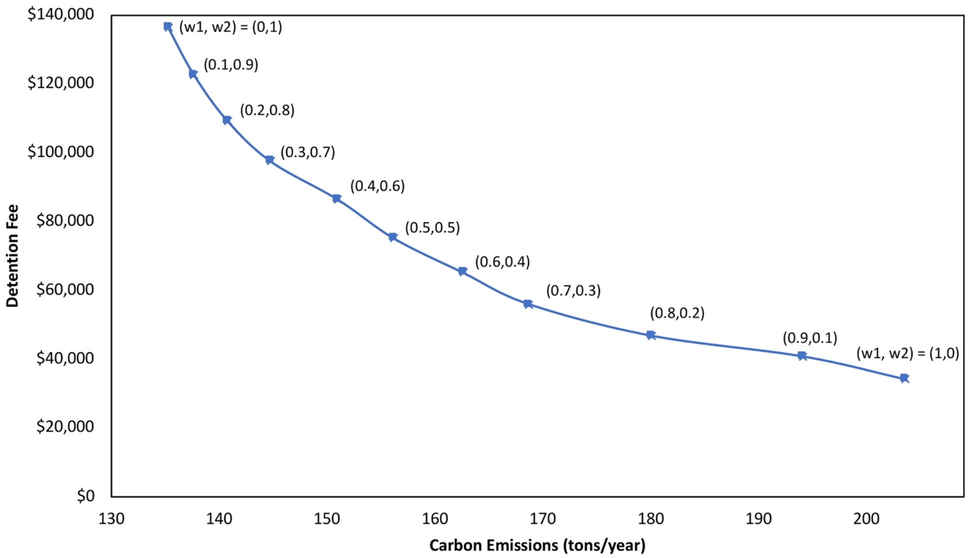


Fig. 8. Impact of varying the weights associated with detention fee (w1) and carbon footprint (w2) in Scenario 3.

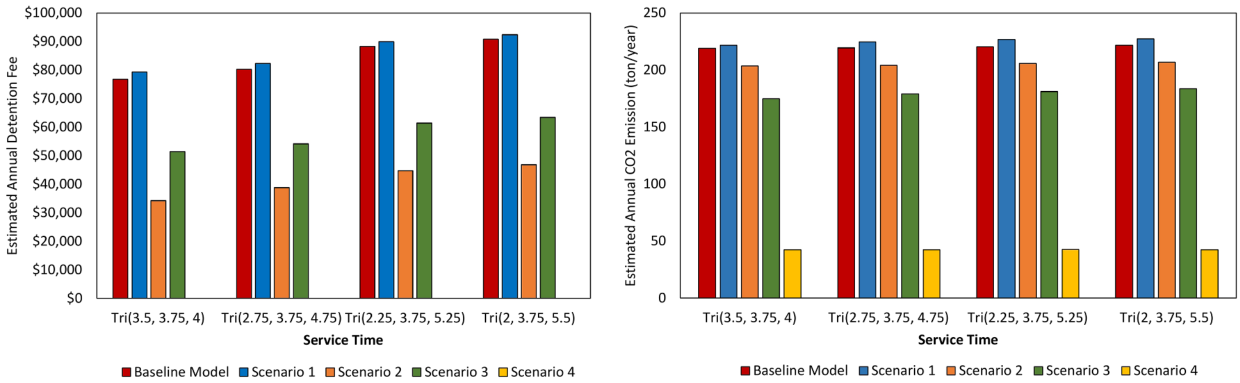


Fig. 9. Impact of service time variation on detention fee and carbon footprint.

7.2. Impact of service time distribution

In the preliminary analysis, the estimates from the time study and domain experts were used to model the check-in processing time as triangular distribution. In this section, we investigate the sensitivity of the service time distribution on detention fee and carbon footprint. Two other distributions for service times, namely, uniform and lognormal, were evaluated by fixing their mean to the most likely value for check-in processing. Further, all the other parameters remain the same as the initial setting. Fig. 10 shows a comparison of the performance measure values for different check-in time distributions.

It can be observed that the initial findings are valid even when the service time distribution is changed. In other words, Scenarios 2–4 dominate the current system irrespective of the service time distribution. For the baseline and alternative models, the performance measures are similar under triangular and uniform distributions but increase significantly for the lognormal distribution.

7.3. Cost-effectiveness evaluation

It is clear from the results presented in the preceding section that reducing the check-in processing time at the main entrance by installing automated kiosks (Scenario 4) is best with respect to detention fees and CO_2 emissions. However, each of the proposed alternatives requires additional investment and increases the total operating costs when compared to the baseline setting. In this section, the incremental cost associated with each scenario is evaluated. The cost breakdown of implementing the proposed staging area (Scenario 1) is shown in Table 8.

Implementing the dispatching rules proposed in Scenarios 2 and 3 requires the inclusion of a queue management system, which incurs an additional initial fixed cost of $2000 and an annual maintenance cost of $1800 that is not accounted for in Table 8. Therefore, Scenarios 2 and 3 will each incur a fixed implementation cost of $118,207 and an annual cost of $1800. Table 9 provides the cost of automating the warehouse (Scenario 4) check-in operation, which includes the cost of hardware, software, installation, and ERP integration. In addition, the savings attained as a result of not requiring a full-time check-in guard to manually process the trucks is also considered in the cost analysis.

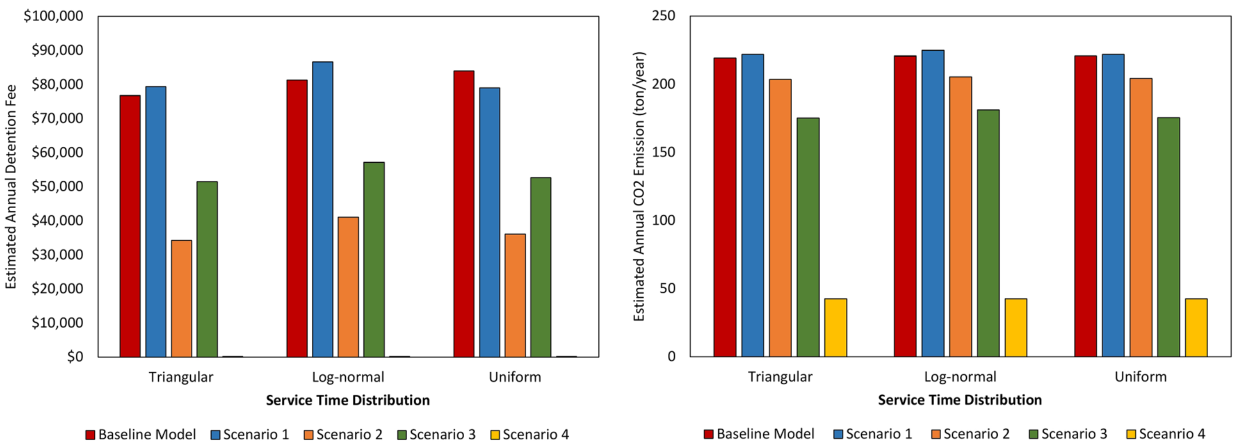


Fig. 10. Impact of service time distribution on detention fee and carbon footprint.

Table 8
Incremental cost calculation for scenario 1.

Cost components	Fixed cost
Cost of concrete pour	
• Land grading	$400
• Sub basing	$12,962
• Concrete reinforcement	$8750
• Concrete delivery charge	$3703
• Concrete pad pour	$90,940
Total cost	$116,207

Table 9
Incremental cost analysis for scenario 4.

Cost components	Fixed implementation cost	Annual cost
Hardware cost		
• Lane hardware	$35,000	$5250
• Portal hardware	$20,000	$3000
Software cost		
• Automated gate system software	$5000	$36,000
• Portal software	$2000	$18,000
Installation cost		
• Installation	$4200	
• Commissioning	$800	
• Training	$1000	
ERP integration cost	$200,000	
Staffing (Savings in worker salary)	–	– $21,000
Total cost	$268,000	$41,250

7.4. Discussion

Each scenario has its potential benefits and drawbacks. In this section, the proposed scenarios will be compared with respect to the cost of implementation, ease of implementation, responsiveness, potential risk, and performance. Furthermore, the discussion is also valid for other similar facilities, and can aid site administrators in choosing the most suitable alternative.

Cost and ease of implementation: Among the proposed alternatives, Scenario 1 requires the least amount of investment for implementation followed by Scenarios 2 and 3, which is slightly more expensive due to the additional investment of a queue management system. As expected, Scenario 4 necessitates the most capital investment as well as annual spending. Before implementing any alternative, its ease of implementation should also be considered as it affects other operations within the facility. Scenarios 1 – 3 may be implemented without disrupting the current operations since the proposed staging area is not impacting the current flow of trucks into the facility. Also, the total time of implementation is reliant on the duration of the concrete pour and the time required for curing. On the contrary, Scenario 4 adds more complexity as the installation of the automated kiosk and other hardware will impede the current flow of trucks arriving at the facility and further magnify the check-in process inefficiency during the installation period. Integration with the current ERP system is another challenging and unpredictable task. While Scenarios 2 and 3 can be implemented by using in-house staffs and resources, Scenario 4 requires the use of a third-party consulting company. After implementation of the automated system, the third-party consulting company may still be required depending on the complexity and presence of unanticipated integrations issues.

Responsiveness: With the growing demand for consumer goods, a warehouse may experience higher arrival rates within the next decade. Scenarios 1–3 do not improve the check-in processing rate and therefore, may still operate close to capacity and incur detention fee. As a result, an increased arrival rate could worsen the detention fee paid to the carriers under these alternatives. However, increased arrival rates never impacted the detention fee under Scenario 4. In other words, Scenario 4 is the only alternative with high responsiveness.

Risk: As supply chains become more complex, potential risks and their repercussions should be considered. Due to all internal warehouse processes being reliant on incoming and outgoing trucks, risks within the check-in processes must be minimal. Scenarios 1–3 have little to no risk as the process will still utilize the workers for a manual check-in. When an automated kiosk serves as a primary mode of check-in (Scenario 4), the risk of hardware or software failure is possible. However, if failure does occur, trucks are able to be processed into the facility from workers at a remote location. This backup system will allow drivers to remotely communicate with a worker without the need for staffing workers at all sites, leaving the system fully automated at the facility level.

Performance: All the proposed scenarios will eliminate the queue build-up onto the city roadways, which is a major cause of concern for any facility. However, Scenario 1 does not achieve any savings with respect to detention fee, while Scenarios 2 and 3 reduce it by 55% and 33%, respectively. Moreover, Scenario 1 slightly increases the CO_2 emission, while Scenarios 2 and 3 achieve

over 7% and 20% improvement in CO_2 emissions, respectively. Scenario 4 dominates the other alternatives as it eliminates detention fees and reduces CO_2 emissions by 80%. Thus, Scenario 4 has the potential to achieve an overall superior performance.

7.5. Managerial implications

Congestion at the main entrance was one of the main reasons for the initiation of this research. The local government is receiving a lot of complaints about the trucks blocking the traffic flow of the residents. Therefore, a simple fix would be to implement the staging area from Scenario 1. This would retain the trucks from spilling onto the road from the main entrance. However, this scenario does not single-handedly reduce detention fees or CO_2 emissions to justify implementation. However, dispatching rules from Scenarios 2 and 3 within the staging area significantly reduced detention fees and CO_2 emissions. The major draw to this scenario is the quick implementation period. The queue management system has a minimal annual cost in addition to the $2000 fixed cost. If the manager is looking for a quick and effective solution, it would be in their best interest to use one of the dispatching rules presented in Scenarios 2 and 3 at the staging area.

Adding a check-in kiosk at the main entrance (Scenario 4) was found to have the highest impact on detention fees and CO_2 emissions. This system is capable of handling increased truck arrivals, which makes this scenario a very attractive solution considering the ever-growing demand. Not only is the flow of trucks spilling over from the main entrance reduced, but the waiting line to enter the facility during peak hours is nearly eliminated. A major concern with adding a check-in kiosk is that the drivers are not familiar with this technology. Indeed, there will be a learning curve which will skew the check-in times. However, this variation was shown to have no significant impact on performance measures. While this scenario has its own challenges with respect to implementation, it is also very scalable. Therefore, when adopting it across multiple facilities, the company can lower the implementation cost substantially by leveraging the quantity discounts on the hardware and software, and by managing all the check-in kiosks from one central location using an operator. Thus, in the long-term, this solution would provide the capability to automate check-in process across every facility company-wide further reducing detention fees, CO_2 emissions, and labor costs.

These insights can also serve as a recommendation for other facilities that face similar issues such as high detention fees. The key finding of this study to logistics professionals is that prioritizing trucks for check-in based on their time spent waiting at facility entrance and expected loading/unloading time inside the facility can substantially reduce the annual detention fees. However, emphasizing solely on minimizing detention fee while ordering trucks could result in high CO_2 emissions. Therefore, companies that are inclined towards sustainable development must make a trade-off between CO_2 emissions and detention fee by considering these performance measures in their dispatching sequence. Finally, using a faster check-in process by investing in information technology-enabled devices (e.g., RFID or automated kiosk) could eliminate long queues for check-in, thereby curtailing both detention fees and carbon emissions.

8. Conclusions

The check-in process is a critical stage of the warehouse receiving process and has a huge impact on detention fees and environmental pollution. However, very limited research focused on the operational efficiency of the service check-in process. This research was motivated by a real-life case study of one of the largest consumer goods company in the US, which experienced numerous problems due to inefficient check-in operations – heavy traffic congestion during busy hours, millions of dollars in detention fee every year, warnings from the local government. Therefore, the impact of alternative check-in policies on traffic congestion and environmental pollution was modeled using discrete event simulation.

We proposed four scenarios - construction of a staging area for truck queuing (Scenario 1), combining staging area with a single-attribute dynamic dispatching rule (Scenario 2) and multi-attribute dynamic dispatching rule (Scenario 3), and automation for faster check-in (Scenario 4). Upon verifying and validating the simulation model, the proposed alternatives were developed and evaluated using three key performance measures, namely, truck queue spillover onto the city roads, detention fees, and CO_2 emissions. Scenarios 2 – 4 were found to be better than the current system with respect to the performance measures. A detailed analysis of the proposed alternatives was presented by considering different criteria (cost and ease of implementation, responsiveness, risk, performance), and the short-term and long-term recommendations were deduced by making a trade-off among these criteria. In the era of highly efficient supply chains, the proposed alternatives could aid the supply chain practitioners to gain a competitive advantage by designing a robust receiving process. Future research could aim to integrate the proposed dispatching rules with appointment-based arrivals. While some previous studies consider appointment-based arrivals to be ineffective, combining it with the proposed dispatching rules could lead to fruitful results.

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References

[1] Bureau of Transportation Statistics, Economic Characteristics of the Freight Transportation Industry, Bureau of Transportation Statistics, 2017 from https://www.bts.gov/bts-publications/freight-facts-and-figures/freight-facts-figures-2017-chapter-5-economic.

[2] M. Kiani Moghadam, J. Sayareh, A. Saeed Nooramin, A simulation framework for optimising truck congestions in marine terminals, J. Marit. Res. VII (2010) 55–70.

[3] A Maguire, Stephanie Ivey, Mihalis Golias, M.E. Lipinski, Relieving congestion at intermodal marine container terminals: review of tactical/operational strategies, Proceedings of the Fifty-First Annual Transportation Research Forum 2010, 1 2010, pp. 631–645.

[4] D.J. Bentolila, K. Ziedenveber, R.H. Yehuda, T. Notteboom, Off-peak truck deliveries at container terminals: the “Good Night” program in Israel, Marit. Bus. Rev. 1 (2016) 2–20, https://doi.org/10.1108/MABR-03-2016-0005.

[5] G. Chen, K. Govindan, Z. Yang, Managing truck arrivals with time windows to alleviate gate congestion at container terminals, Int. J. Prod. Econ. 141 (2012) 179–188.

[6] G. Chen, K. Govindan, M. Golias, Reducing truck emissions at container terminals in a low carbon economy: proposal of a queueing-based bi-objective model for optimizing truck arrival pattern, Transp. Res. Part E Log. Transp. Rev. 55 (2013) 3–22, https://doi.org/10.1016/j.tre.2013.03.008.

[7] G. Giuliano, S. Hayden, P. Dell'aquila, T. O'Brien, Evaluation of the Terminal Gate Appointment System at the Los Angeles/Long Beach Ports, METRANS, 2008, pp. 04–06 METRANS project.

[8] A.E. Azab, A.B. Eltawil, A simulation based study of the effect of truck arrival patterns on truck turn time in container terminals, Proceedings of the Thirtieth European Conference on Modelling and Simulation, 2016, pp. 80–86.

[9] N. Li, G. Chen, K. Govindan, Z. Jin, Disruption management for truck appointment system at a container terminal: a green initiative, Transp. Res. Part D Transp. Environ. 61 (2018) 261–273.

[10] E. Zehendner, D. Feillet, Benefits of a truck appointment system on the service quality of inland transport modes at a multimodal container terminal, Eur. J. Oper. Res. 235 (2) (2014) 461–469.

[11] N. Huynh, Reducing truck turn times at marine terminals with appointment scheduling, Transp. Res. Rec. J. Transp. Res. Board 2100 (2009) 47–57. Transportation Research Board of the National Academies, Washington, D.C.

[12] C. Zhou, H. Li, B.K. Lee, Z. Qiu, A simulation-based vessel-truck coordination strategy for lighterage terminals, Transp. Res. Part C Emerg. Technol. 95 (2018) 149–164.

[13] A. Arora, D. Patel, Applying stochastic capacity management to manage truck traffic around a sea port, Proceedings of Hamburg international Conference on Logistics, Hamburg, 2008.

[14] P.J. Egbelu, J.M.A. Tanchoco, Characterization of automated guided vehicle dispatching rules, Int. J. Prod. Res. 22 (1984) 359–374.

[15] T. Le-Anh, M.B.M. De Koster, On-line dispatching rules for vehicle-based internal transport systems, Int. J. Prod. Res. 43 (8) (2005) 1711–1728, https://doi.org/10.1080/00207540412331320481 A. Kamyab, T. Maze, M. Nelson, and B. McCall, Simulation modeling of electronic screening at weigh stations, Transp. Res. Rec. 1613, (1998), 57–62. doi:10.3141/1613-08.

[16] K.H. Kim, J.W. Bae, A look-ahead dispatching method for automated guided vehicles in automated port container terminals, Transp. Sci. 38 (2) (2004) 224–234.

[17] A. Kamyab, T. Maze, M. Nelson, B. McCall, Simulation modeling of electronic screening at weigh stations, Transp. Res. Rec. 1613 (1998) 57–62, https://doi.org/10.3141/1613-08.

[18] C. Liong, C.S. Loo, A simulation study of warehouse loading and unloading systems using arena, J. Qual. Meas. Anal. 5 (2) (2009) 45–56 Retrieved: December 28, 2017.

[19] S. Srinivas, C. Saha, S.W. Yoon, M.T. Khasawneh, K. Srihari, Analysis of campus traffic congestion during move-in days using discrete event simulation, Proceedings of the Society for First Annual World Conference for Industrial and Systems Engineers, 2012.

[20] S. Rajendran, S. Srinivas, C. Saha, Analysis of operations of port using mathematical and simulation modelling, Int. J. Logist. Sys. Manage. 20 (3) (2015) 325–347.

[21] Giovanni Celano, Antonio Costa, Sergio Fichera, Giuseppe Tringali, Linking six sigma to simulation: a new roadmap to improve the quality of patient care, Int. J. Health Care Qual. Assur. 25 (4) (2012) 254–273, https://doi.org/10.1108/09526861211221473.

[22] U.S. Department of Energy – Long-Haul Trucks Idling Burns Up Profits. (2015). Retrieved: October 10, 2018, from DOE/CHO-AC02-06CH11357-1503.